Mobility impact in the spreading of COVID-19 in Ecuador

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Introduction

Ecuador registers around 95,000 confirmed cases and approximately 6,000 deaths, the fourth largest number of cases and fourth largest in number of deaths per million people, after Chile, Peru and Brazil.

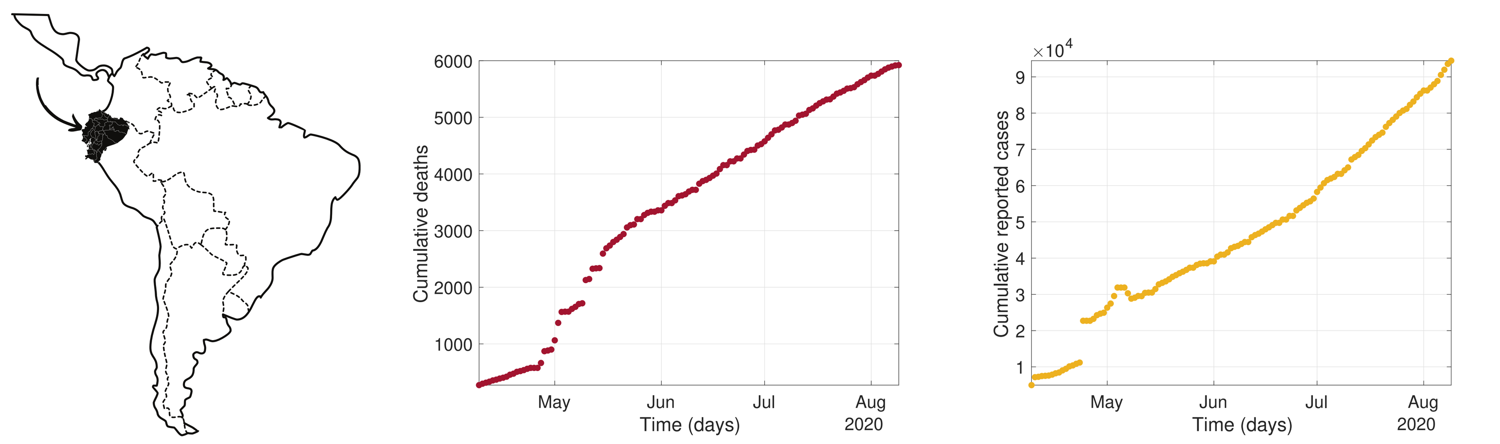

Figure 1: *Location of Ecuador in South America (left), epidemiological curve in Ecuador until August 10 (center) and accumulative deaths in Ecuador until August 10 (right) .*

This study includes a multi-environment model to explore the effectiveness of the traffic light monitoring system, "*traffic lights*" transportation restrictions, where the possible scenarios are best (with no inter provincial movement) and worst (with movement patterns similar to before COVID-19 outbreak) case scenarios in Ecuador. We propose a Multi-patch SEAIR model with Quarantine and Isolation compartments. This study focuses on the spread of Covid-19 infections between eight provinces in Ecuador to study:

- The impact of the transportation restrictions in the number of secondary infections ($\mathscr{R}_c$).
- To asses the impact of the "traffic-lights" policies in the most affected province of Ecuador, until mid July, with limited and unlimited ICU beds (scenarios).

Methods

The model connects its patches, Ecuador's provinces, via a parameter $\psi_{i,j}$ that represents the movement rate from province i to province j. These values are elements of a transportation matrix, which was created from a network whose edges represent the flux of transportation to and from several provinces.

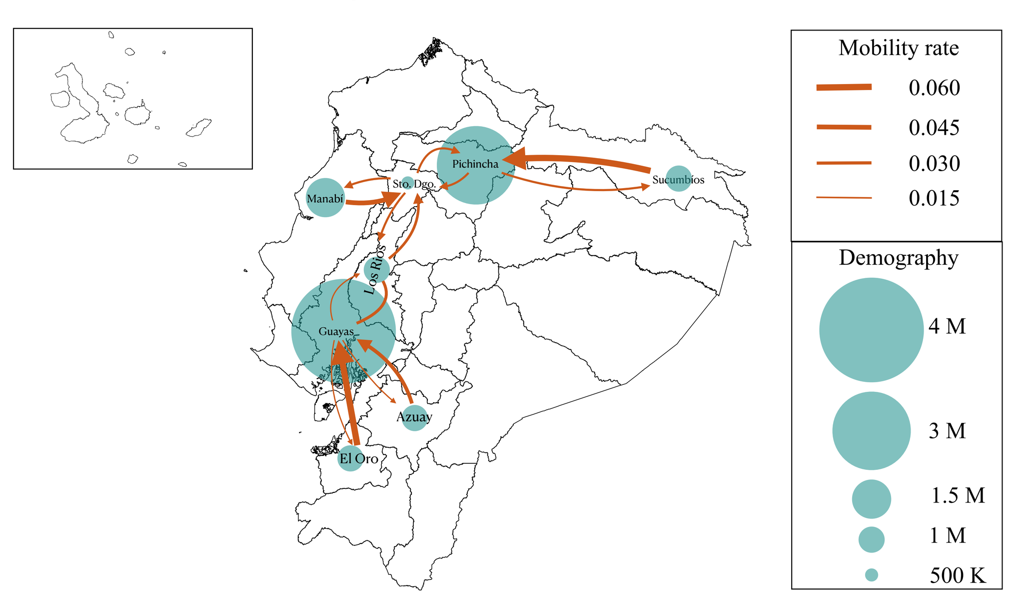

Figure 2: *Transportation network of eight Ecuador provinces, namely Guayas, Manabí, El Oro, Santo Domingo, Los Rios, Sucumbíos, Pichincha and Azuay,*

The transportation process is described, for province i, by the function:

$$\psi_{i,j} = \begin{cases} \dfrac{bp}{Nc}, & \text{if } j \text{ is connected to } i \\ 0, & \text{Otherwise} \end{cases} \qquad (1)$$

where

- $\psi_{i,j}$: Mobility rate from province i to j.
- b: Number of inter-provincial buses.
- p: Number of passengers per bus.
- N: Total population in province i.
- c: Number of direct connections.

We considered a SEAIR (Susceptible-Exposed-Asymptomatic-Infectious Symptomatic-Recovered) type epidemic model with additional features such as closed population (i.e., N is constant) and presence of interventions such as quarantine (Q_1, Q_2, and Q_3), home isolation (Q_4), hospital-isolation (H) and Intensive care unit (ICU, C) classes.

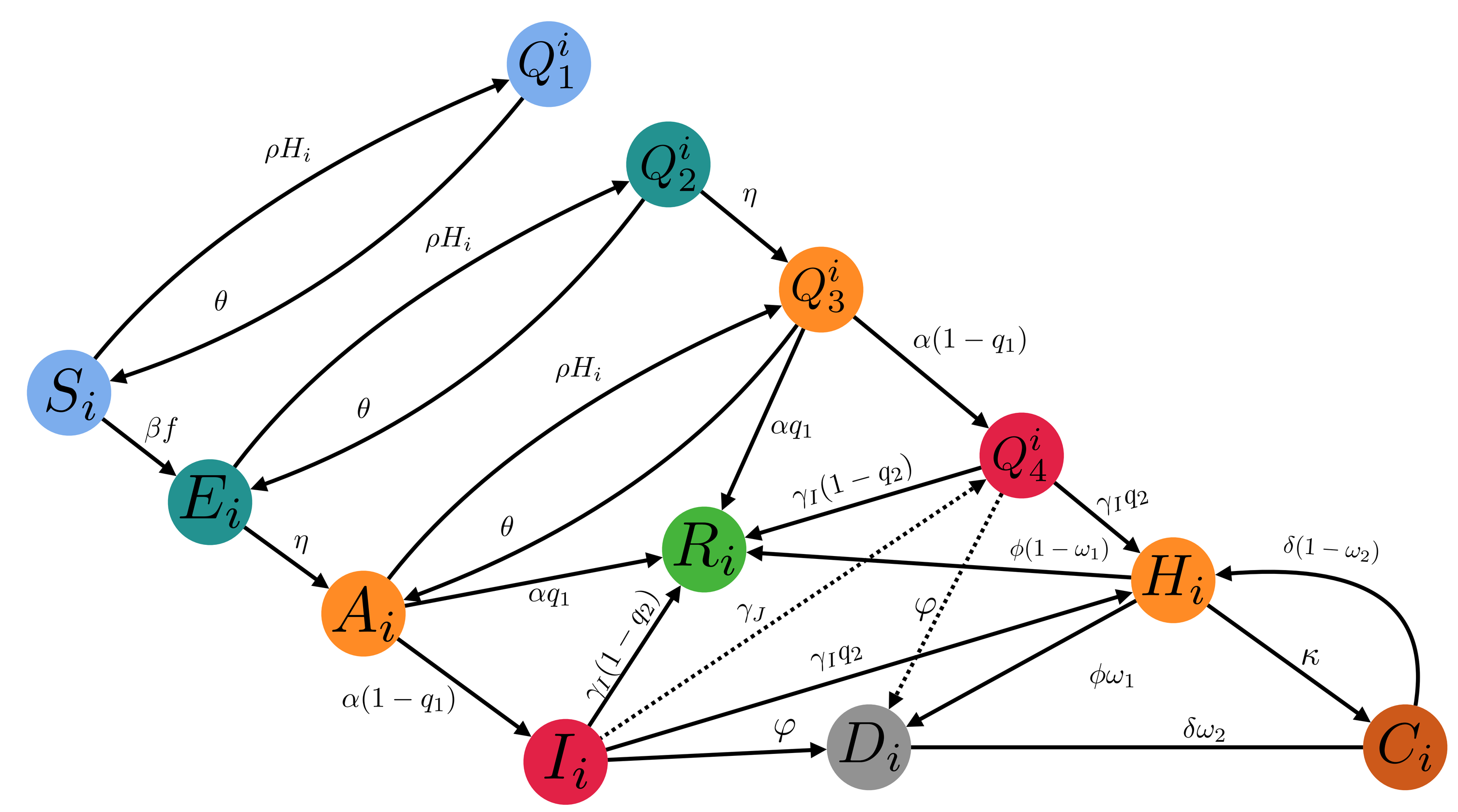

Figure 3: *Schematic flow diagram for our model.*

The force of infection, f, is a nonlinear term given by

$$f = \frac{I + \varepsilon_1 A + \varepsilon_1 l_1 Q_3 + l_2 Q_4 + \varepsilon_2 l_3 H}{S + E + A + I + R + l_1 Q + l_2 Q_4 + l_3 H},$$

where $Q = Q_1 + Q_2 + Q_3$. Moreover, the parameters κ and ω_1 capture limited resources (limited number of ICU beds, C_0) conditions in healthcare facilities and hence,

$$\kappa = \begin{cases} \kappa & \text{if } C(t) < C_0 \\ 0 & \text{if } C(t) \geq C_0 \end{cases} \qquad \omega_1 = \begin{cases} \omega_1 & \text{if } C(t) \geq C_0 \\ 0 & \text{if } C(t) < C_0 \end{cases}$$

Results

The control reproduction number for the multi-patch model, $\widehat{\mathscr{R}}_c$, is given by

$$\widehat{\mathscr{R}}_c = \frac{\beta\epsilon_1\eta}{(\alpha_1 - \widehat{\psi})(\eta - \widehat{\psi})} + \frac{\beta\eta(1-q_1)}{(\eta - \widehat{\psi})(\gamma_I + \gamma_J + \varphi - \widehat{\psi})} + \frac{\beta\eta l_2 (1-q_1)}{(\eta - \widehat{\psi})(\varphi + \gamma_I)} \cdot \frac{\gamma_J}{(\gamma_I + \gamma_J + \varphi - \widehat{\psi})} + \frac{\beta\epsilon_2 l_3 (1-q_1) q_2 \eta}{(\alpha_1 - \widehat{\psi})(\eta - \widehat{\psi})(\kappa + \phi)} \cdot \frac{\gamma_I}{\varphi + \gamma_I}.$$

where

$$\widehat{\psi} = \Upsilon \sum_{j=1}^{n} \psi_{i,j}$$

such that $\widehat{\mathscr{R}}_c > 0$ and finite, $\psi_{i,j}$ represents the mobility rates between provinces i and j and Υ represents the restriction in the movement fixed by the lockdown public policies.

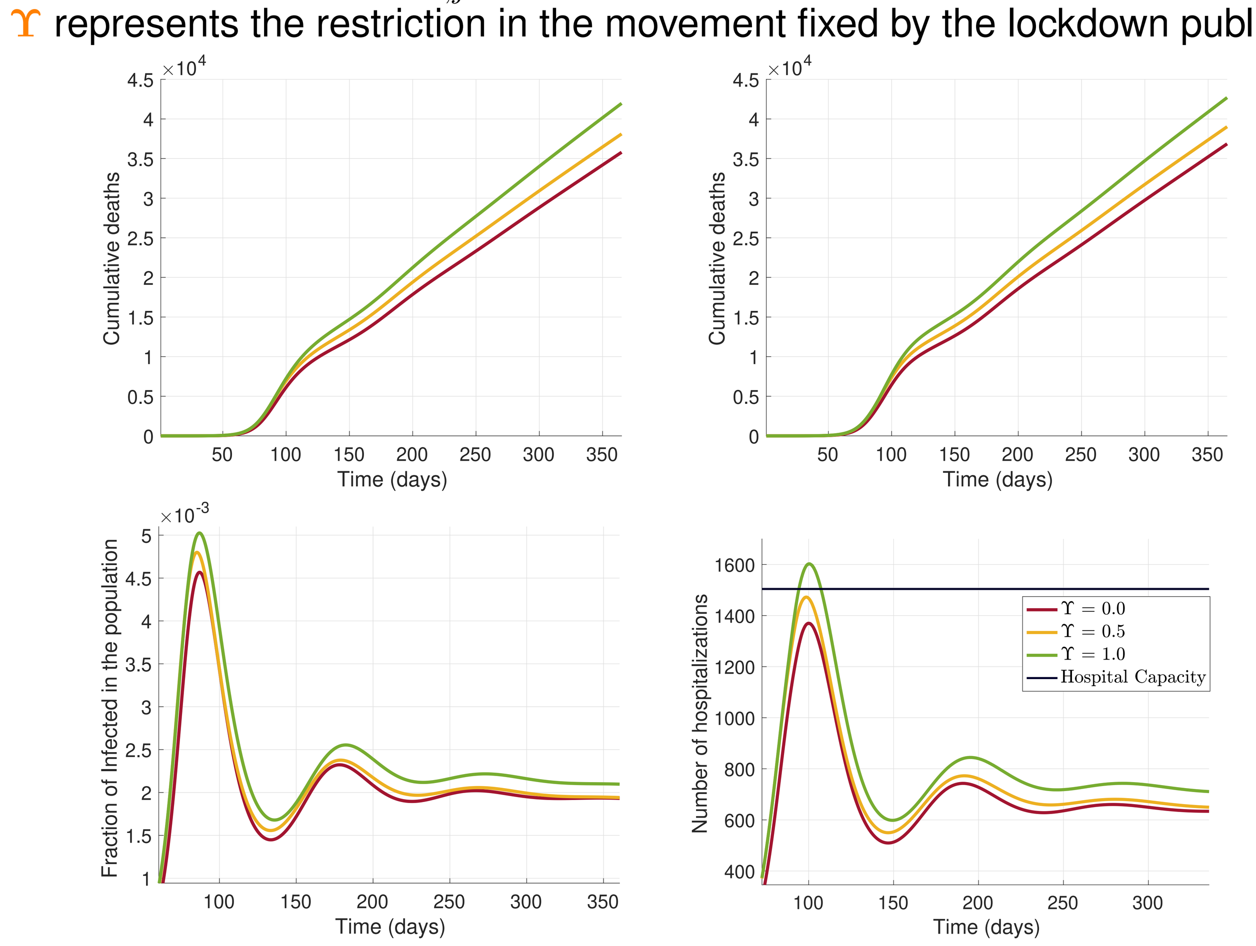

Figure 4: *Cumulative deaths without limited ICU beds (first row left), cumulative deaths with limited ICU beds (first row right), fraction of population whose are infected (second row left) and hospitalizations with limited ICU beds (second row right).*

Conclusion

- The mobility restrictions (Υ) have a direct impact in the number of secondary infections.
- The *traffic-light* transportation restrictions is a public policies that can save thousands of lives. It is more effective than having unlimited ICU beds.